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EXPLORING ISIS' TAKFIR DISCOURSE: A BERT-BASED ENTITY LEVEL
SENTIMENT ANALYSIS APPROACH

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APPROVAL

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15.05.2024



Sevdiklerime,

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ABSTRACT

ISIS has significantly influenced the lives of numerous individuals during and after the Syrian civil conflict, notably impacting civilians. In an effort to understand sentiments expressed towards various volitional entities in their takfir discourse, we endeavored to develop an entity-level sentiment analysis model using computational methods as research on sentiment analysis toward entities, especially in lengthy texts, is limited. To achieve our research objectives, we integrated different models with distinct research purposes. Specifically, we integrated the BERT NER (Named Entity Recognition) model and the two layers of Span ASTE (Aspect-Based Sentiment Analysis). We employed previous scores of Span ASTE as an end-to-end baseline model for comparison. Our hybrid model demonstrated notable improvements over these baselines in precision, recall, and F-scores, suggesting its potential efficacy in sentiment analysis towards entities.

Keywords: Takfir, Span ASTE, LDA, ISIS

ÖZET

IŞİD, Suriye iç savaşı boyunca ve sonrasında birçok bireyin, özellikle de sivillerin, hayatını derinden etkilemiştir. Tekfir anltasında çeşitli karar verebilen varlıklara yönelik ifade edilen duyguları anlamak amacıyla, özellikle uzun metinlerde varlıklara yönelik duygu analizi üzerine yapılan araştırmalar sınırlı olduğundan, hesaplamalı yöntemler kullanarak bir duygu analizi modeli geliştirmeye çalıştık. Araştırma hedeflerimize ulaşmak için, farklı araştırma amaçlarına sahip farklı modelleri entegre ettik. Özellikle, BERT NER modelini ve Span ASTE'nin iki katmanını entegre ettik. Özellikle, Bert NER'i, tipik olarak daha kısa müşteri yorumları için kullanılan yön bazlı bir duygu analizi modeli olan Span ASTE'nin iki katmanıyla birleştirdik. Ayrıca, karşılaştırma için uçtan uca duygu analizi yapan Span ASTE'yi kullandık. Hibrit modelimiz kesinlik, duyarlılık, ve F-skoru açısından bu temel modellerden daha iyi performans göstermiştir.

Anahtar Sözcükler: Kafir, Müşrik, Şirk, Span ASTE, LDA, IŞİD

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LIST OF ACRONYMS AND ABBREVIATIONS

ABSA	Aspect Based Sentiment Analysis
TSA	Text Sentiment Analysis
PER	Person
ORG	Organization
LOC	Location
ELSA	Entity Level Sentiment Analysis
NER	Named Entity Recognition
Span ASTE	Learning Span Level Interactions for Aspect Sentiment Triplet Ex- traction
ISIS	Islamic State of Iraq and the Levant
ASTE	Aspect Sentiment Triplet Extraction
BERT	Bidirectional Encoder Representations from Transformers
NLP	Natural Language Processing
API	Application Programming Interface
ISID	Irak ve Şam İslam Devleti

Here are the abbreviations listed in alphabetical order:

LIST OF ACRONYMS AND ABBREVIATIONS

ABSA	Aspect Based Sentiment Analysis
API	Application Programming Interface
ASTE	Aspect Sentiment Triplet Extraction
BERT	Bidirectional Encoder Representations from Transformers
ELSA	Entity Level Sentiment Analysis
ISID	Irak ve Şam İslam Devleti
ISIS	Islamic State of Iraq and the Levant
LOC	Location
NER	Named Entity Recognition
NLP	Natural Language Processing
ORG	Organization
PER	Person
Span ASTE	Learning Span Level Interactions for Aspect Sentiment Triplet Ex- traction
TSA	Text Sentiment Analysis

1. INTRODUCTION

Since the outbreak of the Syrian civil war, many armed groups of different scales have emerged in Syria and Iraq. Islamic State or ISIS is one of these armed groups claiming statehood in the region and it was highly active between 2014 and 2017. This group adopted a new way of online terrorism(Clifford 2018). Unlike armed groups in the past, they actively used social media as a platform to spread their messages, to attract world-wide attention, to show their strong presence in the area, to recruit fighters etc. The way ISIS utilizes propaganda on its platforms and communicates messages has captured the attention of social researchers. Numerous attempts have been made to comprehend this group, earning it a significant place in the literature on social media studies.

1.1 LITERATURE REVIEW

1.1.1 ISIS AND TELEGRAM

There are a number of researches, with digital ethnographic approaches, analyzing ISIS' propaganda language, group dynamics, daily and cultural practices on social media (Parekh et al. 2018; Alrhoun, Winter, and Kertész 2023; King 2019; Kenyon, Binder, and Baker-Beall 2021; Tønnessen 2017; Bloom, Tiflati, and Horgan 2019). In one of these studies, researchers are interested in how ISIS members and supporters interact and connect to each other on Telegram. One of the topics that the researchers in this study seek to understand is what kind of operational purposes Telegram app serves for ISIS (Krona 2020). To that end, they gathered data from multiple Telegram groups covering a six-month period in 2017. They examined the extent to which ISIS has transformed modern online terrorism by detailing its relationship with its supporters. According to the findings, the way they connect to each other on Telegram is not static. Hence, their interactions there are

both centralized and decentralized based on conditions, subgroups and events. In another digital ethnographic study, the focus was not on the ISIS fighters or ISIS central group dynamics but lone wolves who organize solitary attacks to mainly civilians and Telegram App's role on these attacks (Shehabat, Mitew, and Alzoubi 2017). Four well known ISIS channels are examined for a period of time for that end and the reasons behind telegram usage among these lone wolves attempted to be understood. They suggest that, contrary to other social media platforms, telegram provides some secrecy and this becomes operationally useful for terrorist groups and people to organize attacks. Even whatsapp as a messaging platform never becomes an operational information base for ISIS as it is not trusted by isis members. Another reason to use this platform is other social media platforms' restrictive and censoring actions taken against terrorist groups, especially ISIS but Telegram remained relatively unaffected by this wave of censorship. Suspending accounts is rarely practiced by Telegram management. Therefore, ISIS shifted some of its social media activity from Twitter to Telegram. The fact that Telegram allows its users to create public and private channels eases sharing information for its users. In these channels, there is no limit in the number of subscribers and you can be completely anonymous. ISIS and some other armed groups utilized this feature and used Telegram for operational purposes. It is suggested that this operational convenience may pave the way for lone wolf attacks around the world.

Some studies, instead of focusing on ISIS propaganda they examined ISIS' target audience. One of the studies scrutinized the lives of Western foreign fighters who align themselves with ISIS (Dawson 2021; Kenyon, Binder, and Baker-Beall 2021). The researchers take a close look on western foreign fighters' related works to understand the reasons why they joined ISIS. The commonalities of these fighters' educational, religious, social, and economical backgrounds are checked. thirty-four studies related to foreign fighters are extensively investigated. Based on the data they get from these studies, researchers create detailed and multifaceted profiles of outgoing fighters. The data of this study covers foreign fighters' age ranges, marital status, socioeconomic classes, employment status, motivations, goals, level of religiosity,

criminal records and mental health. Its findings claim that the majority of these people are single. Their average age is around 26, while the age range is wide. It is consistently found that females joining ISIS are younger than the males in this group. The study suggested that the converts are not as high as predicted. It is stated that a few of the fighters are converts. The fighters from western countries are usually from low socioeconomic backgrounds. So these findings side with the studies which relate social and economic marginalization and joining terrorist groups. According to the mental health data of these fighters, no significant differences were observed in their mental health. Lastly, their motivation to join ISIS is varying across the studies, as most of these people have religious upbringings, they usually do not practice religious rituals. This causes debates in the literature on the source of their motivation. In this study, the researchers conclude that even though they are non practitioners, their motivation could be both highly religious and political.

1.1.2 TAKFIR DISCOURSE

Although ISIS employs global propaganda strategies and maintains dynamic ties with supporters worldwide, the majority of those adversely affected by the Islamic State, including casualties, displacements, and fatalities, are members of the Muslim community. In a comprehensive study on the Takfiri approach in Daesh's media, Jamileh Kadivar investigates the historical, cultural, and political motivations behind this strategy (Kadivar 2020). Kadivar traces the concept of "takfir" back to its historical roots, noting its emergence with the Khawarij in the post-Quranic period and its significant shaping by theologians such as Ibn Taymiyyah and Ibn Abd al-Wahhab.

Kadivar explains that Daesh's use of takfir extends beyond non-Muslims to include a wide array of Muslims who do not conform to its strict interpretation of Islam. This includes targeting both Sunni and Shi'a groups, as well as other Islamic factions like the Muslim Brotherhood, thereby branding them as apostates or heretics (Kadivar 2020). This tactic serves to delegitimize and violently suppress these groups.

Through detailed analysis of Daesh’s media outputs, Kadivar demonstrates how takfir is employed in their propaganda to promote a binary worldview, separating Daesh supporters from those labeled as kuffar. This ”othering” process is central to Daesh’s identity and strategy, embedding ideological messages deeply within their communications.

Furthermore, Kadivar highlights internal conflicts within Daesh concerning the application of takfir, revealing divisions between more extreme and less extreme interpretations within the organization. This study underscores the ideological differences between Daesh and other jihadist groups, such as Al-Qaeda, and shows how takfir has become a pervasive tool in Daesh’s propaganda arsenal (Kadivar 2020).

Takfir: The practice of declaring another Muslim as an infidel or non-believer (*kafir*), thereby justifying violence or exclusion against them.

1.2 NATURAL LANGUAGE PROCESSING TECHNIQUES FOR SOCIAL MEDIA ANALYSIS

As we delve into analyzing ISIS’s takfir discourse on social media, it’s crucial to understand the foundational NLP techniques that enable this analysis. This section provides an overview of the key NLP techniques used in social media analysis, focusing on machine learning, deep learning, sentiment analysis, and opinion extraction.

1.2.1 MACHINE LEARNING

Machine learning techniques are foundational in NLP for social media analysis. They include both supervised and unsupervised learning methods:

- **Supervised Learning:** Support Vector Machines (SVM), Naive Bayes, and Decision Trees are frequently employed for classifying social media posts into specific categories. These supervised learning models rely on labeled datasets, which are typically annotated manually to demonstrate various classes or cat-

egories (Alpaydin 2020; Bishop 2006)

- **Unsupervised Learning:** Clustering methods such as K-means and topic modeling techniques like Latent Dirichlet Allocation (LDA) are used to uncover patterns and group similar social media posts without predefined labels. These approaches are especially valuable for analyzing large datasets to detect trends and emerging topics (Murphy 2012; Blei, Ng, and Jordan 2003).

1.2.2 DEEP LEARNING

Deep learning has revolutionized NLP by enabling the development of more sophisticated and accurate models for social media analysis:

- **Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM):** Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are tailored for sequential data processing, making them ideal for tasks like sentiment analysis and opinion mining on social media platforms (Hochreiter and Schmidhuber 1997; Graves and Graves 2012)
- **Convolutional Neural Networks (CNNs):** Convolutional Neural Networks (CNNs) were initially developed for image processing tasks but have been successfully adapted for text classification by capturing local patterns in textual data. This adaptation leverages CNNs' ability to recognize spatial hierarchies, which is beneficial for identifying key phrases and n-grams in text (Kim et al. 2014; Zhang, Zhang, and Vo 2015).
- **Transformers and BERT:** Transformers, particularly the Bidirectional Encoder Representations from Transformers (BERT) model, mark a significant advancement in Natural Language Processing (NLP). BERT's capacity to comprehend context and nuance in text has made it highly effective for numerous NLP tasks, such as entity recognition and sentiment analysis (Devlin et al. 2018; Vaswani et al. 2017).

1.2.3 SENTIMENT ANALYSIS

Sentiment analysis aims to determine the sentiment expressed in social media posts, categorizing them as positive, negative, or neutral. Techniques used in sentiment analysis include:

- **Lexicon-Based Approaches:** Lexicon-based approaches involve using pre-defined dictionaries containing sentiment-laden words to assess the sentiment of posts. Each word in the lexicon is assigned a sentiment score, contributing to the overall sentiment evaluation of the text (Liu et al. 2012)
- **Machine Learning-Based Approaches:** Machine learning-based approaches for sentiment analysis involve training classifiers on labeled datasets to predict the sentiment of new posts. These approaches utilize both traditional machine learning models such as Support Vector Machines (SVMs) and Logistic Regression, as well as advanced deep learning models like Long Short-Term Memory (LSTM) networks and Bidirectional Encoder Representations from Transformers (BERT) (Pang, Lee, et al. 2008; Devlin et al. 2018)

In our research, we used BERT in combination with Span ASTE to improve the accuracy of sentiment analysis towards specific entities.

1.2.4 OPINION EXTRACTION

Opinion extraction focuses on identifying and summarizing opinions from social media posts, which is essential for understanding public sentiment and discourse. This involves:

- **Aspect-Based Sentiment Analysis (ABSA):** Aspect-Based Sentiment Analysis (ABSA) focuses on identifying particular aspects or features of a subject, such as a product or service, and determining the sentiment expressed towards each aspect. Models like Span ASTE (Aspect Sentiment Triplet Extraction) are utilized to pinpoint aspect terms, opinion expressions, and sentiment po-

larities (Pontiki et al. 2016; Xu, Chia, and Bing 2021).

- **Named Entity Recognition (NER):** Named Entity Recognition (NER) is essential for identifying entities such as persons and organizations mentioned in social media posts. Integrating NER with sentiment analysis aids in understanding opinions directed at specific entities (Nadeau and Sekine 2007; Lample et al. 2016).

Our approach integrates these techniques to build a comprehensive model for analyzing ISIS’s takfir discourse, enabling us to understand sentiments expressed towards various volitional entities in their communications.

1.3 ENTITY LEVEL SENTIMENT ANALYSIS(ELSA)

1.3.1 PROBLEM STATEMENT

In this paper, we aimed to explore ISIS’ takfir discourse on some Telegram groups through computational methods (Powell and Menendian 2016). We have opted to construct a computational model for sentiment analysis and detection in social media, drawing from the discourse analysis of ISIS in existing literature and theoretical frameworks.

Although computational sentiment analysis research is extensive in the literature, the literature on sentiment analysis toward specific entities is limited. A large part of this limited literature consists of models created for short-text customer reviews(Zhang et al. 2021; Chehal, Gupta, and Gulati 2021; Li et al. 2023; Banjar et al. 2021). In addition to the limited scope of existing literature, there exists a terminological inconsistency within the field. Various terms are used interchangeably, and identical cases are described using different terminology. This inconsistency diminishes the clarity of the subject and its research endeavors.

A study addressing the terminological inconsistency proposes the term ELSA for Entity Level Sentiment Analysis (Rønningstad, Velldal, and Øvrelid 2023). This

study draws attention to the diverse usage found in existing literature and proposes a pool of terms to address this variability, aiming to foster consistency in future research and enhance clarity by employing terms that effectively encompass the multi-layered nature of the topic.

Entity-Level Sentiment Analysis (ELSA) is an emerging research area that aims to determine the overall sentiment directed towards specific volitional entities, including persons and organizations, within a document (Rønningstad, Velldal, and Øvreliid 2023). Traditional sentiment analysis methods, which work well for short texts like tweets, often fall short when applied to longer texts with multiple mentions and opinions towards the same entity. These researchers conducted a series of experiments to explore how existing sentiment analysis tools can be adapted for ELSA.

The findings of the study highlight that key sub-tasks for effective Entity-Level Sentiment Analysis (ELSA) include Named Entity Recognition (NER), which identifies and classifies entities in text; Coreference Resolution, which links different mentions of the same entity; Targeted Sentiment Analysis (TSA), which determines sentiment toward specific targets; and Target-Entity Resolution, which identifies the specific entity associated with each sentiment target (Rønningstad, Velldal, and Øvreliid 2023).

Their research also suggests that sentiment in longer texts is often expressed through both direct mentions and contextual references, requiring advanced techniques to resolve these complexities. By integrating NER, coreference resolution, and TSA, they developed a framework for ELSA that improves upon traditional sentiment analysis methods.

In our study of ISIS's takfir discourse on social media, we adapt this approach by using BERT for NER to identify entities and Span ASTE for extracting sentiment towards these entities. This combined approach enables us to capture the nuanced sentiment dynamics within ISIS-related social media content more accurately.

The work by Rønningstad et al. provides a valuable framework for our analysis, helping us to structure our sentiment analysis effectively. By addressing the challenges identified in their study, we aim to enhance the accuracy and reliability of our analysis of sentiments towards volitional entities in ISIS’s takfir discourse. We also intend to incorporate the terminology pool of this study into our work as it captures the existing literature well and offers a more nuanced understanding, especially on lengthy texts (Figure 1.1).

ENTITY LAYER	OPINON EXPRESSIONS	SENTIMENT POLARITY
Volitional Entities Entity Mentions	Target expressions - Sentiment Targets - Aspect Targets Polar Expressions - Polarities - Polar Intensities	Polarity - NEG, POS, NEU Intensity - Mainly Likert type measurements (Ex. giving a number between 1-6 based on intensity)
<i>Sit-ins are the kind of demonstrations of the democrats, and those who strongly advocate them are the bankrupt ikhwan.</i>	<i>Sit-ins are the kind of demonstrations of the democrats, and those who strongly advocate them are the bankrupt Ikhwan.</i>	<i>Sit-ins are the kind of demonstrations of the democrats, and those who strongly advocate them are the bankrupt Ikhwan.</i>
Ikhwan --> Volitional Entity Democrats ---> Entity Mentions	Sit-ins --> Aspect Target Demonstrations --> Aspect Target Bankrupt --> Polar Expression	Ikhwan --> Negative Democrats ---> Negative Strongly --> Polar Intensity
Some Tasks - Entity Detection - Resolution of Entity Mentions	Some Tasks - Target-Entity Resolution - Identifications of Sentiment Targets	Some Tasks - Classification of Sentiment Polarity - Calculation of Sentiment Intensity

Figure 1.1 Terminology of ELSA

The nuanced nature of measuring sentiments toward some entities in lengthy social media messages of an armed group necessitates a hybrid approach and task-specific modifications. Span ASTE is one of the models that perform sentiment analysis on short texts (Xu, Chia, and Bing 2021). It is specialized for analyzing customer reviews on products or services, focusing on specific parts of the text called ‘spans.’ Despite its high accuracy in short texts, its performance decreases with longer opinion lengths.

Research Questions:

1. How can we effectively detect relevant volitional entities, persons, and organizations, in lengthy Telegram messages?
2. What are the methods to accurately identify opinions towards these volitional entities?

3. How can we determine the sentiment polarity of these opinions in the context of ISIS takfir discourse on Telegram?

1.3.2 RESEARCH APPROACH

The Span ASTE model, originally created for short text analysis, was adapted to meet our research requirements. Our study aims to detect sentiments toward volitional entities, such as persons (PER) and organizations (ORG), using Named Entity Recognition (NER) models. This focus rendered an end-to-end implementation within the traditional Span ASTE framework, usually applied to products and services, unsuitable for our purposes (Xu, Chia, and Bing 2021)

To address our research questions, we adopted the following approach:

- **Entity Identification:**
 - We utilized the first layer of the Span ASTE model, customized to extract aspect terms relevant to our study.
 - For this layer, we used one of the main NER models called **Bert Base NER** (Tjong Kim Sang and De Meulder 2003).
 - With NER tasks, it is possible to capture various entities, but we only included volitional entities relevant to ISIS' takfir narrative.
- **Opinion Extraction:**
 - Opinions were extracted using span analysis, where the model identifies and links different expressions referring to the same entity.
 - This includes resolving pronouns and other referring expressions (**Coreference and Anaphora Resolution**).
- **Sentiment Analysis:**
 - Sentiment polarity was determined by evaluating the contextual relationships between the extracted opinions and their respective entities within the Telegram data.

Our model, visualized in Figure 1.2, illustrates the integration of NER for entity

detection and span analysis for opinion extraction and sentiment classification.

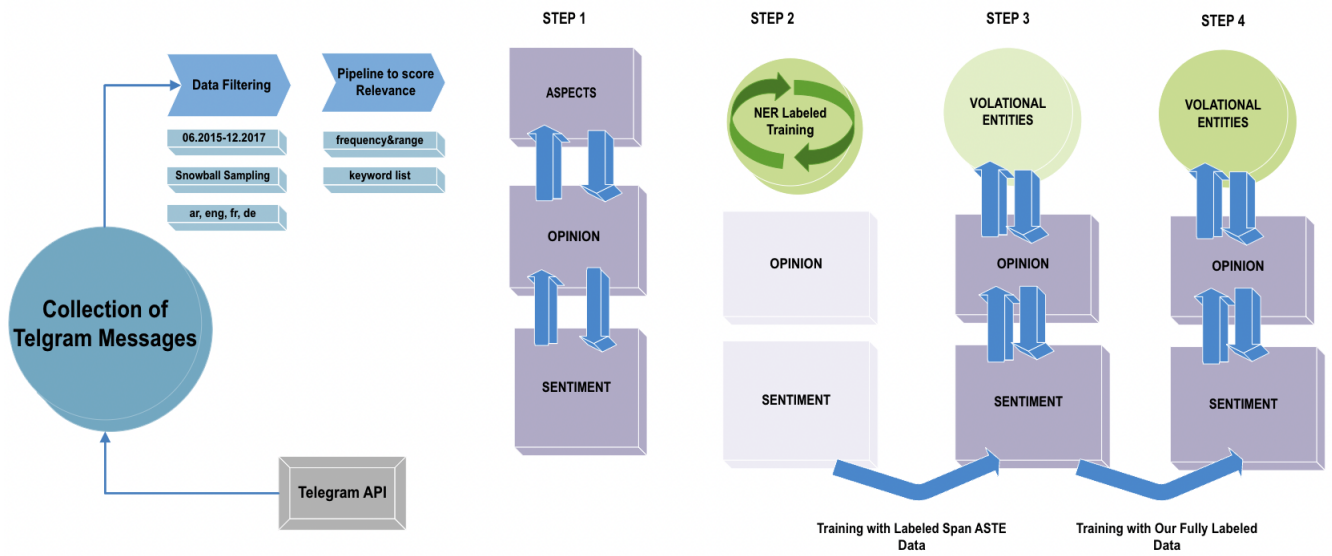


Figure 1.2 Our Hybrid Approach

The example sentence in Figure 1.3 demonstrates the application of our approach, addressing the following main tasks:

1. Identifying volitional entities
2. Extracting opinions related to these entities
3. Analyzing sentiment polarity using our Telegram data

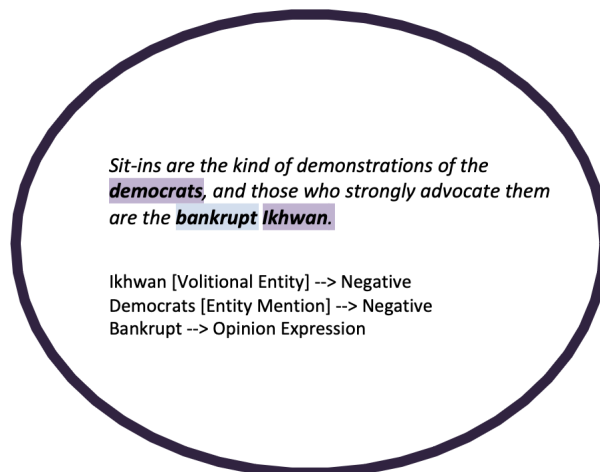


Figure 1.3 Example

1.4 THESIS OUTLINE

This thesis is structured to systematically explore the takfir discourse of ISIS using a BERT-based entity-level sentiment analysis approach.

The Methodology chapter describes the process of gathering data from Telegram channels, detailing the criteria for selecting relevant chats and messages associated with ISIS. It explains the construction of the hybrid sentiment analysis model, integrating the BERT Named Entity Recognition (NER) model and the Span Aspect Sentiment Triplet Extraction (ASTE) model. The data preprocessing steps are outlined, including the identification of relevant entities and opinions, and the determination of sentiment polarity.

The Results chapter presents the statistics of the collected data, including the number of messages, entities, and sentiments identified. It provides the evaluation metrics of the hybrid model, comparing its performance to baseline models using precision, recall, and F-scores. This section also includes an analysis of the sentiments expressed towards different volitional entities (persons and organizations) in the ISIS takfir discourse.

The Discussion begins with a summary of the findings, highlighting key results from the analysis. It then explores the factors contributing to low performance scores in the model, offering insights into the challenges encountered during the research. This section also discusses the contributions of the study, detailing the novel insights and advancements made in the field of entity-level sentiment analysis and its application to extremist discourse. The limitations of the study are acknowledged, categorized into topic-related, methodological, and study-specific constraints.

The Conclusion summarizes the key findings of the research, discussing their implications for counter-terrorism and sentiment analysis research. It discusses future research directions, suggesting areas for further exploration to enhance the model's performance and applicability. Finally, the section reflects on the broader implica-

tions of the study, particularly its potential impact on counter-terrorism strategies and the understanding of extremist narratives.



2. METHODOLOGY

In our methodology, we first concentrate on devising strategies to gather the appropriate data, a crucial step for the overall success of the study.

2.1 GETTING DATA AND TELEGRAM API

Primarily, we compiled a seedlist using ISIS literature and archives, resulting in a small list of possibly ISIS-related chats(Krona 2020). Subsequently, we employed this seedlist for snowball sampling. While only some of these seeds were associated with ISIS supporters, the rest were involved in sharing news about the Syrian civil war. Given the informative nature of these channels, we assumed that ISIS members might follow and interact with them. Therefore, our goal was to identify ISIS-related channels through these seeds.

After determining the seedlist, six telegram apps with the necessary API's and tokens are created to crawl the data. Even though Telegram Management freely provides apis, the daily crawling amount is limited. So data extraction had to be spread out over a period of time.

In the snowball sampling part, we benefited from the messages forwarded to our seed accounts in the first layer. Layer by layer, we traced the chat ids of interacting chats through this method. At the end, we created a pool of chat ids. Although initially, we crawled all chat IDs, we later excluded some of them based on specific conditions we set beforehand.

The first condition we set was time-related. Given that ISIS activity on social media platforms peaked between 2015-2017, we focused on channels active at any time within that period. Additionally, we only included accounts that produced

content in English, Arabic, German, and French, considering potential difficulties that may arise in handling other languages in NLP part.

2.1.1 KEYWORDS AND RELEVANCE PIPELINE

After compiling the chats' ids, we implemented our second pipeline to identify ISIS supporter or sympathizer groups more precisely. In this pipeline, we created a list of words likely to appear in Islamic State's propaganda texts, members' messages, and daily conversations. We employed various approaches to collect these keywords.

Initially, we manually selected potential ISIS indicator words from the propaganda texts of Dabiq magazine, ISIS ran journal, publishing content during the active and influential period of ISIS. (Shehabat, Mitew, and Alzoubi 2017). In addition to that, since ISIS propaganda content is actively banned and censored on many platforms, we focused on Justpaste.it and archive.org, two platforms where completely anonymous content is still possible and rarely removed.

Some of the keywords we identified include:

- Aqidah
- Salafi
- Sharia
- Qaeda
- Commander
- Dabiq
- Nashir
- Sheikh
- Muwahid
- Abu Dawala
- Haqq
- Jihad
- Ummah
- Caliphate
- Mujahideen
- Amaq
- Isdarat
- Kufr
- Kuffar
- Gazwa
- Mujahid
- Shirk
- Baghdadi

This second pipeline is designed to assign a relevance score to each chat. It takes into account the frequency of keywords in the texts, the size of the texts, and the diversity of keywords used. While some chats may contain many of these words, the highscoring chats underwent a manual inspection to ensure they were not merely informational channels providing news. The chats producing mostly visual or audio content were also excluded. In the end, we selected ten chats among around five hundred chats that met the conditions set. Nine of these chats were in Arabic and

one of them was in English. They consist of around fourteen thousand messages sent between the specified time period.

2.1.2 DATASETS

- **Telegram Chats Dataset:** This dataset consists of messages from Telegram groups identified through our snowball sampling method. We compiled a list of chat IDs, focusing on those active between 2015-2017 and producing content in English, Arabic, German, and French. The final dataset includes around fourteen thousand messages.
- **Pretrained Datasets:** For initial testing and fine-tuning, we used datasets such as 14lap, 14res, 15res, and 16res, which are part of the Span ASTE model. These datasets include reviews related to restaurant services and laptops.

2.2 ELSA BERT

Initially, as a baseline, we labeled long messages at the entity, opinion and sentiment level. In the first step, we directly tested the pretrained Span ASTE model with our dataset without any training process. After that, we subsequently fine-tuned the model with the model pretrained with 15res (Xu et al. 2020). The datasets called 14lap, 14res, 15res, 16res are the main datasets of Span ASTE model. While 14res, 15res, 16res include the reviews related to restaurant services, 14lap dataset is about Laptop reviews. We used these fine-tuning scores namely precision, recall and f-score for comparison as a baseline to evaluate our model.

After having the baseline values, we finally started the modelling part. This part is divided into three. The first part is related to extracting correct entities using Named Entity Recognition. On the second part, we trained our model which is pretrained at the NER step with the 15res dataset. And finally on the third step, we trained the whole pretrained model with our fully labeled dataset. With each step, we updated the parameters.

On the NER step, to extract relevant entities, we applied Bert Base NER on fourteen thousands telegram messages (Table 2.1). Then, we excluded the entities whose model score is less than 0.6. After that, we filtered out entities which has more than 4 words as the model has a limited span length. The location and miscellaneous entities labeled as LOC and MISC were also removed. Finally, we manually excluded the misclassified entities. At the end, we had around one thousand two hundred messages with ORG and PER labels. Afterwards, we trained the first layer of Span ASTE model and froze the last two layers related to opinion and sentiment. We increased the span length from 8 to 12 with the intention of analysing our lengthy data more accurately. To train this layer with our labeled data, we divided our data into train, test, and validation sets with ratios of around 60%, 15%, and 25%, respectively.

Description	Value
Number of Messages	14476
Number of Characters	12830684
Groups in Arabic	9
Groups in English	1

Table 2.1 NER Data Before Preprocessing

On training with the 15res dataset step, as our focus is on training the model with relational information, we updated the loss weights parameters. There are two loss weight parameters. The first one is related to entity extraction and the other one is related to the relation. As we aim to teach relational information, we updated the hyperparameters accordingly.

After the whole model is prepared for the third step, we fine-tuned our model with our fully labeled data which contains 95 messages and 209 entities. This is the main part of the study. Afterwards, we evaluated the performance of this step by comparing it with our baselines.

Data	# of Epochs	Hidden Dimensions	# of Layers	Dropout	NER Loss Weight	Relation Loss Weight	Max Span Width
NER	4	200	1	0.4	2	0	12
15res	4	150	2	0.4	0.2	1.8	8
Labeled	10	200	2	0.4	1	1	12

Table 3.1 Hyperparameters

3.1.1 NER

The dataset that we used for NER consists of 1212 messages and 2403 entities. The mean length of the messages and entities are 1.32 and 179 respectively Figure 3.2. After preparing the data, we need to connect the messages and entities to train the model. To do this, we add the start and end indexes of the entities to the data. In this way, our model can understand which part of the message between which indexes is an entity. After this step, we split the data into three sets: train, test, and validation. We use the `train_test_split` function of the sklearn library for this splitting process. The approxiamet ratios of the datasets are as follows: train: 0.6, test: 0.2, validation: 0.2. Some of these entities can be seen on Figure 3.3

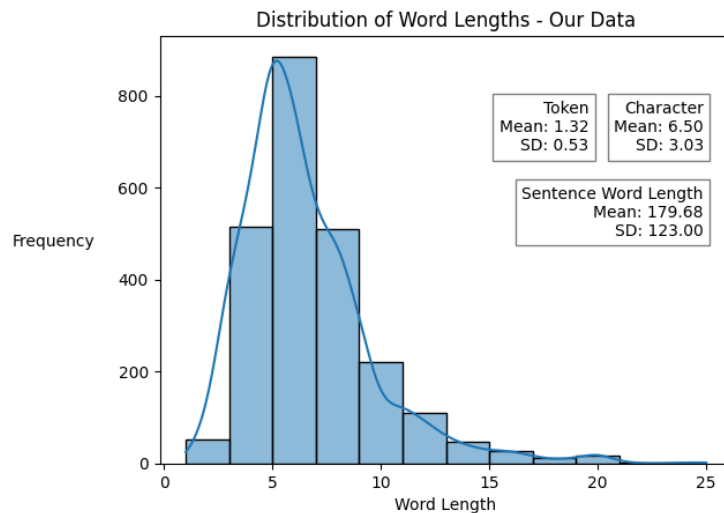


Figure 3.2 NER Data Summary

We reduced the number of train epochs in the trainer parameters from 10 to 4 due to the size of the data and time constraints. In this way, our model will be trained faster. Other parameters remained the same except for these parameters, these parameters are also shown on Table 3.1.

3.1.2 15RES

Specifically, to train the relation layer, we use the fully labeled 15res dataset. The start and end indexes of entities and opinions are already added to it and the dataset is already split into three sets: train, test, and validation. The average entity and sentence lengths of this dataset are indicated on Figure 3.4 and Figure 3.5.

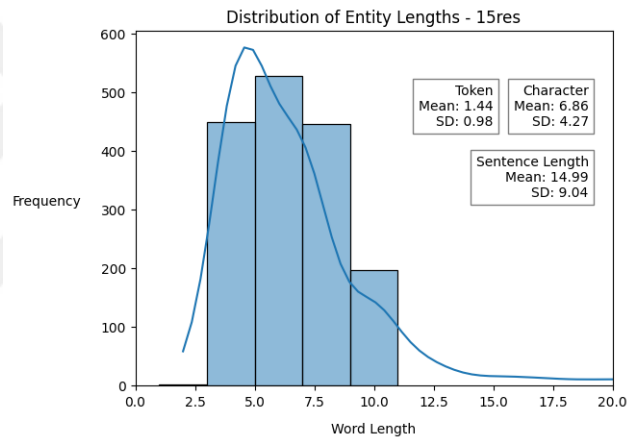


Figure 3.4 15res Entity Summary

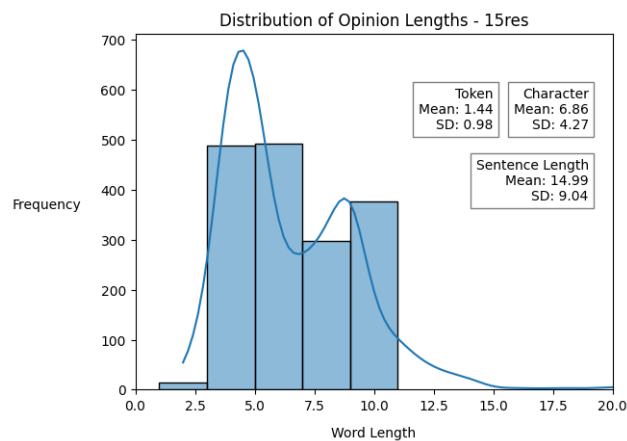


Figure 3.5 15res Opinion Summary

We used the parameters of the span aste model as this dataset is its base dataset and it is already trained and tested with the model and came up with the good



Figure 3.7 Example Entity Words of 15res

3.1.3 MAIN DATA

After training our model with these two steps, we finally trained it again with our fully labeled data. In this dataset, the average length of the messages, opinions and entities can be seen in Figure 3.8, Figure 3.9 and Figure 3.10. As in other parts, we added the indexes in a way that is aligned with the Span aste format. Some of the opinions and entities in this dataset could be seen on this figure. In addition to that, in this dataset, 140 entities are labeled as NEG, 60 of them as POS, and lastly 4 of them as NEU which is shown on Figure 3.11. Some examples of opinions and entities can be found on Figure 3.12 and Figure 3.13. Based on the characteristics of this dataset, we updated the parameters here too. Specifically, we

updated the feedforward, loss weights, feedforward, and module parameters in the model parameters.

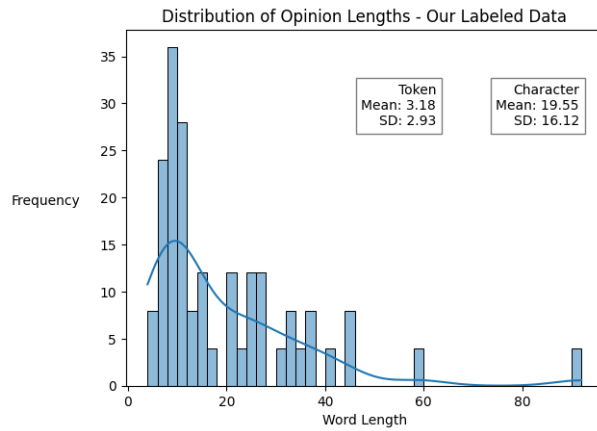


Figure 3.8 Opinion Words Summary

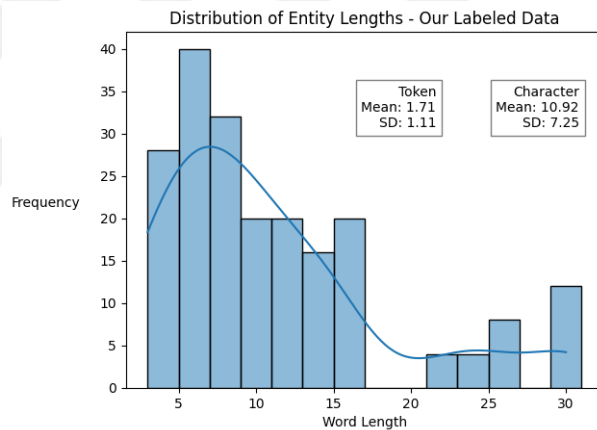


Figure 3.9 Entity Words Summary

We increased the number of hidden dimensions in the feedforward parameters to 200 and keep the number of layers as 2 as we are interested in both NER and relation information here. For a balanced training, we keep the loss weights parameter as

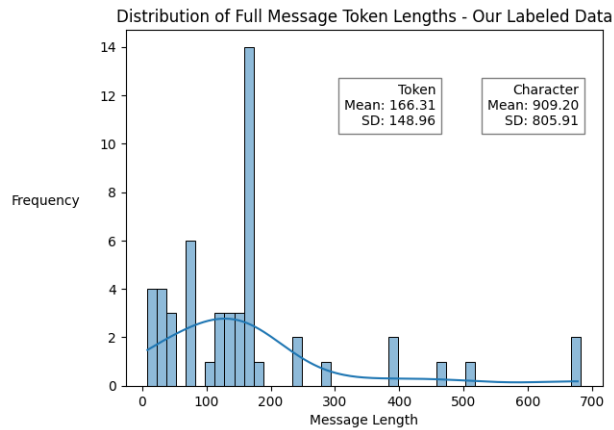


Figure 3.10 Message Length

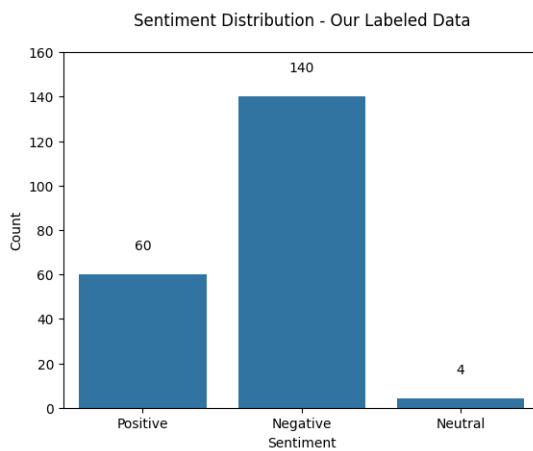


Figure 3.11 Our Data - Sentiment

1 for both NER and relation parts. We increased the max span width from 8 to 12 as we have longer texts in this part.

In the first two parts, we set the number of epochs to 4. In this part, since the data is smaller and this dataset is the only part that contains fully labeled chat messages, it is important to increase the learning while training. So we set the number of epochs to 10.



Figure 3.12 Labeled Data Entity Examples

3.2 ANALYSIS

3.2.1 BASELINES

Upon evaluating the Span-ASTE model directly on the test data, distinct performances were observed across various datasets. For the 14lap dataset, the model exhibited a precision of 0.182, with a comparatively lower recall of 0.035, resulting in an F-score of 0.059. Similarly, for the 14res dataset, the precision was recorded at 0.167, with a slightly higher recall of 0.053, culminating in an F-score of 0.08. Notably, the model showcased improved precision and recall on the 15res dataset, achieving values of 0.355 and 0.105, respectively, yielding an F-score of 0.164. Conversely, for the 16res dataset, the model attained a precision of 0.3 and a recall of 0.088, leading to an F-score of 0.149.

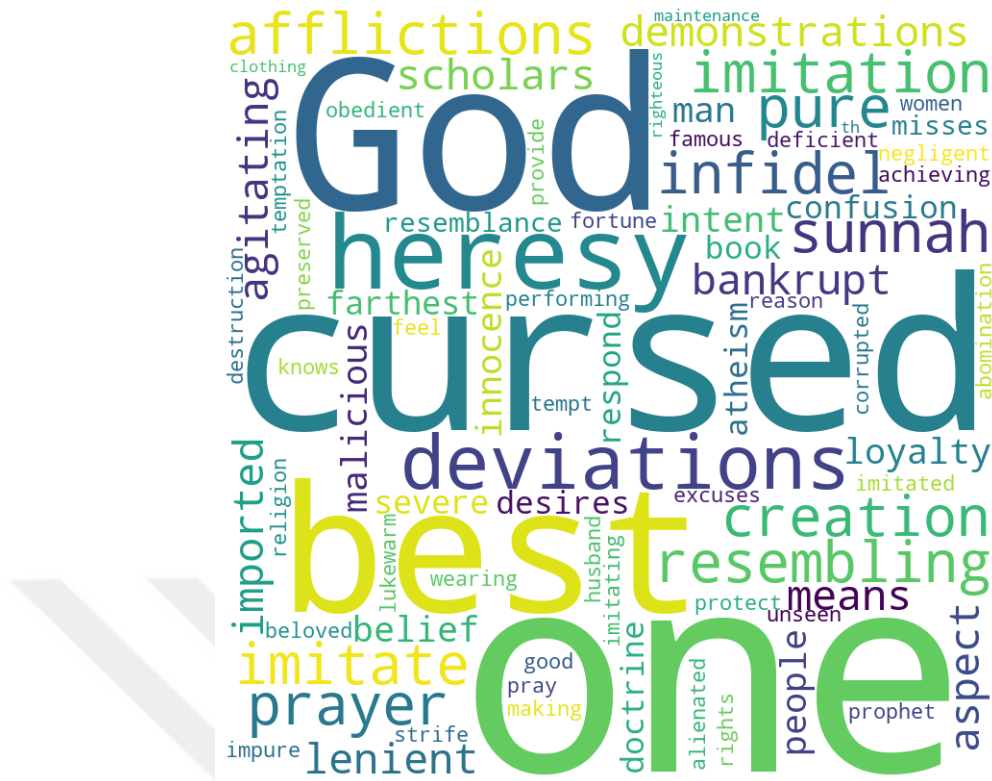


Figure 3.13 Example Opinion Words

3.2.2 MODEL

After training our pretrained model with our own fully labeled data, we evaluated our model on the test data. In this section, we observed that we performed better than other models. Our Hybrid model performed best with an F1 score of 0.493. While the recall value was 0.596, the precision value was 0.420. Based on these results, this hybrid approach performed better than baselines in all F1 score, precision, and recall as it is shown on Table 2.1.

	14lap	14res	15res	16res	mixed data	our model
Precision	0.181	0.167	0.335	0.3	0.37619	0.419
Recall	0.0351	0.052	0.105	0.0877	0.212766	0.596
Score	0.0589	0.08	0.164	0.1492	0.2941	0.492

Table 3.2 Performance Table

4. DISCUSSION

4.1 SUMMARY OF FINDINGS

The results show that although fine-tuning the model helps, the best results are yielded when we separately trained the first layer from scratch. The performance notably improved even though the dataset we labeled on three levels was highly limited. I assume these results could improve even more with an increase in data size.

Our baseline models performed poorly on every case when we pretrained with model's base datasets. The F1 scores of the baseline models were 0.059, 0.08, 0.164, and 0.149 for the 14lap, 14res, 15res, and 16res datasets, respectively. The precision and recall values of the baseline models were also low. The precision values of the baseline models were 0.182, 0.167, 0.355, and 0.3 for the 14lap, 14res, 15res, and 16res datasets, respectively. The recall values of the baseline models were 0.035, 0.053, 0.105, and 0.088 for the 14lap, 14res, 15res, and 16res datasets, respectively. Among all these pretraining cases, our dataset performed best with the model pretrained with 15res dataset. So we used this dataset to teach our model relational information. We used different parameter values to train the model. Since our texts are more complex and have a richly cited structure, we observed that increasing the hidden dimensions improved the performance. Also, since there are longer texts, we checked the performance by increasing the max span width. Increasing the span width allowed the model to look at a wider window, so we achieved better results.

Since the SpanASTE model is focused on finding aspects rather than entities, the entity extraction performance was low. Therefore, we aimed to achieve better results by extracting entities with the NER model. Then, on the second step, we aimed to achieve better results by adding the relationship information learned from the 15res dataset to our model trained only on entities. Finally, we trained and tested our

model with all of our data. This model gave us the best result; however, the final outcome was still relatively low compared to ABSA models applied to short-text customer reviews.

4.2 FACTORS CONTRIBUTING TO PERFORMANCE SCORES

Several factors likely contributed to the lower performance scores observed in our study. One significant challenge is the nature of our dataset, which likely contains informal and potentially ungrammatical language typical of noisy social media texts. This can complicate sentiment analysis as these texts do not adhere to standard linguistic rules, making it difficult for models to parse and interpret sentiments accurately. The specialized vocabulary and jargon specific to ISIS's discourse may not be well-represented in general sentiment analysis models, and training these models requires extensive and high-quality annotated data, which may have been limited in our study.

Additionally, our research involves open domain sentiment analysis, which introduces unique challenges. Unlike domain-specific models, such as those focused on customer reviews, open domain models must handle a broader range of topics and linguistic styles. This lack of specificity makes achieving high accuracy more challenging. In domain-specific sentiment analysis, models can leverage well-established patterns and repetitive language structures typical of the domain, such as the frequent use of specific adjectives and phrases in product reviews to express satisfaction or dissatisfaction (Luo et al. 2022).

In contrast, open domain sentiment analysis requires the model to be versatile and adaptable to a wide array of linguistic variations and contextual nuances. This adaptability often leads to a trade-off between the model's breadth and its depth of understanding. For instance, while a domain-specific model might excel at identifying subtle nuances in customer feedback due to its focused training, an open domain model may struggle to capture similar subtleties across diverse topics. This

is because open domain models must generalize across many different contexts, potentially diluting their sensitivity to the unique linguistic cues of any single context.

The length and complexity of the sentences in our dataset further complicate the analysis. The Telegram messages we studied often contain lengthy, intricate, and ideologically loaded content related to ISIS’s Takfir discourse. This is in stark contrast to the short, straightforward texts typically used in sentiment analysis, where sentiments are more easily discernible. The rich context and nuances within these messages mean that sentiments are often implied or subtle, requiring a more sophisticated understanding to interpret accurately.

Domain-specific challenges also play a significant role. The specialized vocabulary and jargon specific to ISIS’s discourse may not be well-represented in general sentiment analysis models. While we utilized a domain-specific approach with BERT-based NER and Span ASTE models, training these models effectively requires extensive and high-quality annotated data, which may have been limited in our study.

Moreover, our focus on entity-level sentiment analysis (ELSA) adds another layer of complexity. Identifying and linking sentiments to specific entities within the same text is inherently more challenging than determining the overall sentiment of a text. This requires the model to not only recognize the sentiment but also correctly associate it with the relevant entity, a task that demands a high level of precision and contextual understanding.

4.3 CONTRIBUTIONS

4.3.1 NOVEL INTEGRATION OF NLP MODELS

Our research introduces a novel approach to sentiment analysis using Natural Language Processing (NLP) models. We combine the BERT Named Entity Recognition (NER) model with Span ASTE (Aspect-Based Sentiment Analysis) to analyze sentiments towards volitional entities in lengthy texts. This integration addresses a

challenge that has received limited attention in previous studies.

4.3.2 IMPROVEMENT IN SENTIMENT ANALYSIS PERFORMANCE

The hybrid model we developed shows significant improvements in performance compared to baseline models. It achieves higher precision, recall, and F-scores, indicating its effectiveness in accurately detecting and analyzing sentiments towards entities.

4.3.3 METHODOLOGICAL CONTRIBUTIONS

Our research may also contribute methodologically by establishing a framework for data collection and preprocessing techniques from Telegram chats. This framework could serve as a reference for future studies analyzing social media data for sentiment and discourse analysis.

4.4 LIMITATIONS

There are several limitations to this study. The research topic itself is highly nuanced, necessitating multiple layers of analysis. Conducting a multilayered analysis using BERT requires significant processing power. We were unable to train our model on different datasets due to this limitation, and we had to limit the size of our datasets to reduce processing time. Additionally, despite increasing span length to better capture relationships, there is still room for improvement in linking entities and entity mentions, particularly in longer texts. This task becomes more crucial as the data contains comprehensive discourse with numerous opinions on various matters. Furthermore, since we did not use different datasets due to processing power limitations, there is a risk that our model may overfit our dataset and perform poorly on other datasets with similar characteristics, such as longer texts with nuanced structures.

5. CONCLUSION AND FUTURE WORK

In recent years, researchers employing Natural Language Processing (NLP) methods have increasingly opted to use BERT due to its high accuracy rates in various language understanding tasks. BERT's ability to incorporate different layers to meet specific task requirements makes it adaptable and a preferred choice for many researchers across different fields. Research focusing on social media dynamics, particularly involving marginalized groups like ISIS, is becoming more prominent. The application of such methods has broadened across a spectrum of fields, including those where their utilization has been less conventional.

In this study, we aimed to analyze the propaganda language used by ISIS, identifying entities throughout the text and the sentiments toward them. Our goal was to develop a specific model that could be applied to similar studies, providing insights into the dynamics related to the ideological framing of radicalization.

5.1 ELSA FOR TAKFIR DISCOURSE

We utilized the BERT Base NER and Span ASTE Model. Our primary challenge was incorporating volitional entity extraction into the Span ASTE framework. To address this, we trained the initial layer of the Span ASTE model while keeping the subsequent two layers frozen, and then trained the entire model with our labeled data.

This study explored ISIS' takfir discourse using a BERT-based entity-level sentiment analysis model. By combining the BERT Named Entity Recognition (NER) model with the Span ASTE (Aspect-Based Sentiment Analysis) layers, we aimed to create a hybrid model that could improve upon baseline models in precision, recall, and F-scores. Our model performed better than the baselines, suggesting that integrating

BERT’s capabilities in entity recognition with Span ASTE’s approach to aspect-based sentiment analysis enhances overall performance. The BERT NER model was employed to accurately identify and classify entities within the discourse, such as individuals and organizations, which are pivotal in understanding the sentiments expressed towards them. This allowed for a more targeted and contextually relevant sentiment analysis.

The Span ASTE layers contributed by analyzing specific aspects of the discourse and determining the sentiment polarity associated with each identified entity. This layered approach enabled a more granular analysis, distinguishing between positive, negative, and neutral sentiments in a way that simpler sentiment analysis models cannot achieve. The ability to extract and analyze sentiment at the aspect level provided deeper insights into the nuanced and often complex language used in ISIS’ takfir discourse.

Our hybrid model demonstrated improved performance metrics, such as better precision, recall, and F-scores, indicating its potential effectiveness in handling the complexities of lengthy and context-rich texts. These results suggest that the model could be useful for broader applications, including the analysis of other forms of extremist discourse or any domain that requires detailed sentiment analysis of complex textual data.

Overall, the integration of BERT NER and Span ASTE models in this study contributes to the field of sentiment analysis and offers a useful tool for understanding the narratives used by extremist groups like ISIS. This research provides insights that may be valuable to both computational linguistics and counter-terrorism studies by presenting a method for examining and interpreting sentiment dynamics within radical narratives.

5.2 FUTURE DIRECTIONS

By specifically analyzing the takfir discourse of ISIS, we have created a reference model that could be applied to similar studies and groups, providing insights into the dynamics related to the ideological framing of radicalization.

Building on the findings of this study, future research can take several directions to further enhance the understanding and analysis of ISIS' takfir discourse:

- **Expanding the Dataset:**

- Increasing the size and diversity of the dataset will help improve the model's robustness and applicability.
- This can include incorporating texts from different periods, languages, and platforms.

- **Improving Entity Linking:**

- Refining the methods for linking entities and mentions across longer texts will be crucial.
- Advanced techniques in coreference resolution and entity linking should be explored to enhance this aspect of the model.

- **Exploring Other Extremist Groups:**

- Applying the model to analyze the discourse of other extremist groups can provide comparative insights.
- This will broaden the understanding of how different groups use language for radicalization and propaganda.

5.3 IMPLICATIONS

The findings of this study on ISIS' takfir discourse using a BERT-based entity-level sentiment analysis model have several significant implications for research, policy, and practical applications. These implications span various domains, including counter-terrorism efforts, natural language processing (NLP) advancements, and

social media monitoring.

5.3.1 COUNTERING EXTREMIST PROPAGANDA

Our study could have practical implications for understanding and countering online extremist propaganda. By analyzing the sentiments and targets of ISIS takfir discourse, more effective strategies for monitoring and countering extremist activities online can be developed.

5.3.2 ADVANCEMENTS IN NATURAL LANGUAGE PROCESSING (NLP)

- **Improvement in Sentiment Analysis Models:** The successful integration of BERT NER with Span ASTE layers demonstrates the potential for developing more sophisticated sentiment analysis models. This advancement can be applied to various domains beyond terrorism research, including customer reviews, social media analysis, and political discourse.
- **Entity-Level Analysis:** The focus on entity-level sentiment analysis provides a more nuanced understanding of sentiments towards specific entities. This approach can be extended to other research areas where understanding the sentiments towards individuals, organizations, or other entities is critical.
- **Handling Complex and Lengthy Texts:** The study's approach to analyzing lengthy and complex texts can be applied to other contexts where traditional sentiment analysis models fall short. This advancement can improve the analysis of texts in legal documents, academic papers, and other detailed narrative formats.

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APPENDIX A: TITLE OF THE FIRST APPENDIX

The appendices start here.



Suheda Yildirim

Data Scientist

Languages: English (C2), Turkish (Native), German (B1), French (A2)

EXPERIENCE

1) Georg-August Universität | Abteilung Forschung & Transfer (03.2023-Current)

Part Time Data Scientist

Technologies & Skills: Python, Full Stack Web Development, Django, Docker, Mongo, Pandas, Docker, Gitlab, Django, Nginx, Pandas, PostgreSQL, SSH, MongoDB, Web Scraping, Beautiful Soap, Database Systems

Goals: Scraping academic data of the university from multiple non-api websites. Full Stack Web Development. Creating a web app to make institutions and researchers data available to students and researchers.

2) Max Planck Institute - Dynamics and Self-Organization

Paid Research Assistant

Project: Examining Covid-19 Related Disinformation on Telegram

Technologies & Skills: Python, Sql, MySQL, Numpy, Scikit-learn, Pandas, NLP, LDA, Spacy, Text Classification, Data Preprocessing, Social Media Analysis, Statistical Analysis

Goals: Implement Natural Language Processing (NLP) techniques and network analysis to identify the dissemination patterns of Covid-19 misinformation on Telegram. Develop models using Python to quantify the impact of key influencers and detect community structures within the network.

3) Utrecht University - Department of Information and Computing Sciences

Unpaid Internship

Project: Automated Confidence & Academic Humility Detection In Scientific Papers

Technologies & Skills: Python, Machine Learning, Statistical Analysis, Text Classification, LIWC, Data Visualization

Goals: Develop machine learning models for the detection of confidence and humility indicators in scientific papers. Use NLP algorithms such as BERT for text classification and implement data preprocessing pipelines to handle large corpora of academic texts.

4) Kadir Has University - Management Information Systems Department

Paid Research Assistant

Project: Digital Public Diplomacy of Armed Organizations – Syria and Iraq Cases

Technologies & Skills: Python, Matlab, R

Goals: Conduct comprehensive data analysis using NLP and network analysis to study the digital public diplomacy strategies of armed groups in Syria and Iraq. Develop models to analyze their social media usage patterns and leverage R and Python for statistical analysis and visualization of the data.

Master Thesis

Project: A BERT-Based Entity Level Sentiment Analysis Approach

Technologies & Skills: Python, Sql, Gephi, BERT, Telegram API, Social Media Analysis, Text Classification, Data Preprocessing, Sentiment Analysis, Deep Learning, Data Visualization

Goals: Design and implement a BERT-based sentiment analysis model for entity-level analysis of Telegram data. Develop scripts for data scraping and preprocessing

EDUCATION AND COURSES

Master of Digital Humanities , Göttingen University, <i>Göttingen</i>	2022 - Present
<ul style="list-style-type: none">• Courses; Network Analysis with Gephi (Python), Analyzing Social and Cultural Data (Python), Computing meaning in Premodern Text (Python), Computational Literary Studies	
Master of Management Information Science , Kadir Has University, <i>Istanbul</i>	2020 - 2023
<ul style="list-style-type: none">• Courses; Data Mining, Machine Learning, Neural Networks, and Fuzzy Systems, Introduction to Data Science Tools, Multivariate Data Analysis, Data Analytics, Database Design and Management	
Kodluyoruz Data Science for the Public Good Bootcamp , <i>Istanbul</i>	2020 - 2021
Bachelor of Psychology , Boğaziçi University, <i>Istanbul</i>	2013 - 2017
<ul style="list-style-type: none">• Bachelor degree (Highly interdisciplinary curriculum esp. including statistics, calculus courses)	

ACADEMIC ACHIEVEMENTS

- **Ranked in the top thousand** in the nation-wide university entrance exam among 1.5 million candidates, primarily due to **exceptional performance in the math test**. This test covered a wide range of topics including Linear Algebra, Limits, Integrals, Derivatives, Trigonometry, Quadratic Equations, Polygons, Solid Geometry, Trigonometric Functions, Probability, Exponential and Logarithmic Functions, Sequences, Trigonometry, Continuity.
- **Ranked in the top hundred** in the nation-wide Turkish GRE exam among two hundred thousand candidates, **excelling in both text comprehension and highly analytical problem-solving math questions**.